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ANALYSING THE DYNAMICS OF INDONESIAN BANKS' PERFORMANCE UNDER ARTIFICIAL INTELLIGENCE ADOPTION: AN EMPIRICAL AND SIMULATION APPROACH

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Abstract

This study analyses the impact of artificial intelligence (AI) on bank performance and financial stability in Indonesia using a combined empirical and simulation approach. Employing monthly panel data from 50 Indonesian banks during the period 2017–2023, the empirical analysis applies Feasible Generalised Least Squares (FGLS) and staggered Difference-in-Differences (DiD) estimators following Callaway and Sant'Anna to identify the effects of AI adoption. The results show that AI adoption increases Return on Assets (ROA) by 0.116 percentage points and reduces Non-Performing Loans (NPLs) by 0.068 percentage points, while AI chatbot implementation raises ROA by 0.189 percentage points and lowers the Loan-to-Deposit Ratio (LDR) by 3.18 percentage points. In contrast, AI training is associated with a short-run decline in ROA, reflecting implementation and adjustment costs. Staggered DiD estimates indicate that bank performance weakened during the COVID-19 period due to heightened liquidity pressures but stabilised in the post-pandemic phase, thereby contributing to improved financial stability. Complementing the empirical findings, a system dynamics simulation demonstrates that AI investments initially constrain profitability growth but yield accelerating gains over time through efficiency improvements and risk mitigation. Overall, the study highlights the importance of phased AI adoption and institutional readiness in strengthening bank performance and financial stability in Indonesia.

Keywords: *artificial intelligence, bank performance, Indonesia, financial stability, difference-in-differences*

I. INTRODUCTION

The digital transformation in the Indonesian banking sector has forced several industry players to adapt to emerging challenges.[1] As part of the broader digital transformation in the Indonesian banking sector, the adoption of artificial

[1] A. Riyanto et al., "Digital Branch: Banking Innovation in Indonesia to Face 4.0 Industry Challenges," *IOP Conference Series: Materials Science and Engineering* 662, no. 7 (2019): 6, https://doi.org/10.1088/1757-899X/662/7/072002.

intelligence (AI) eases use and reduces customers' perceived risks.[2] Meanwhile, the Indonesian workforce varies in digital literacy levels, creating obstacles to adopting technologies that support banking performance.[3] However, annual reports from several Indonesian banks indicate broad adoption of AI and AI training for their workers. Since 2018, many annual reports have shown that private banks in Indonesia with large assets under management, including CIMB Niaga, BCA, and OCBC NISP, have already adopted AI technology through AI chatbots and AI training for their employees. With these industry steps, customer satisfaction can be increased through better, more accessible digital services.[4]

From a regulatory standpoint, technological transition in banking intersects with macroprudential supervision and systemic stability. Technology can improve banking performance. Previously, Gyau et al.[5] found that AI technology led to better banking performance. Amato et al. also explained that AI use in credit management could improve the bank's performance.[6] Given its potential impact on banks' credit risk and profitability, Bank Indonesia should oversee AI implementation in banking to ensure the stability and soundness of the national banking system amid the recent trend of AI adoption.

Although the adoption of AI in the Indonesian banking sector has shown significant progress in recent years, empirical research relevant to domestic banking conditions remains relatively limited. Most previous studies have used cross-country samples or focused on institutional contexts outside Indonesia,[7] thus failing to fully capture differences in regulatory characteristics, the maturity level of AI implementation, and the readiness of national banking

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2 Ridho Bramulya Ikhsan et al., "An Empirical Study on the Use of Artificial Intelligence in the Banking Sector of Indonesia by Extending the TAM Model and the Moderating Effect of Perceived Trust," *Digital Business* 5, no. 1 (2025): 3–5, 100103, https://doi.org/10.1016/j.digbus.2024.100103.

3 Elisa Indriasari et al. "Digital Banking: Challenges, Emerging Technology Trends, and Future Research Agenda," *International Journal of E-Business Research* 18, no.1(2022): 9, https://doi.org/10.4018/IJEBR.309398.

4 Nofie Iman et al., "Is Technology Truly Improving the Customer Experience? Analysing the Intention to Use Open Banking in Indonesia," *International Journal of Bank Marketing* 41, no. 7 (2023): 1521–24, https://doi.org/10.1108/IJBM-09-2022-0427

5 Emmanuel Baffour Gyau et al., "Transforming Banking: Examining the Role of AI Technology Innovation in Boosting Banks' Financial Performance," *International Review of Financial Analysis* 96 (2024): 1–2, 103700, https://doi.org/10.1016/j.irfa.2024.103700

6 Alessandra Amato, Joerg R. Osterrieder, and Marcos R. Machado, "How Can Artificial Intelligence Help Customer Intelligence for Credit Portfolio Management? A Systematic Literature Review," *International Journal of Information Management Data Insights* 4, no. 2 (2024): 4–5, https://doi.org/10.1016/j.jjimei.2024.100234

7 Ekene S. Aguegboh et al., "ICT Adoption, Bank Performance & Development in Sub-Saharan Africa: A Dynamic Panel Analysis," *Information Technology for Development* 29, no. 2-3 (2022): 406, https://doi.org/10.1080/02681102.2022.2131701.

organisations. In addition, previous literature tends to emphasise profitability indicators, particularly Return on Assets (ROA) and Return on Equity (ROE),[8] while the impact of AI on credit risk and banking intermediation functions, as reflected in Non-Performing Loans (NPLs) and Loan-to-Deposit Ratio (LDR), has been relatively under-explored. These limitations indicate that previous research has not fully explained the heterogeneity in the impact of AI adoption in the Indonesian banking industry.

Responding to this gap, this study examines banking in Indonesia with a focus on the adoption of AI technology, such as the use of AI chatbots, other AI features, and AI-based human resource training, and their implications for banks' performance. Specifically, this study poses three main research questions. First, how does AI adoption affect banking profitability, credit risk, and intermediation efficiency as measured by ROA, NPLs, and LDR? Second, to what extent are these effects dynamic and change over time, especially in the face of economic shocks such as the COVID-19 pandemic? Third, how does the long-term interaction between AI investment and banking financial performance evolve within a dynamic framework? Answering these questions is important for understanding whether the benefits of AI are sustainable or entail short- and long-term adjustment costs and trade-offs.

To comprehensively answer these research questions, this study offers methodological innovation by combining an empirical approach through Feasible Generalised Least Squares (FGLS) and staggered Difference-in-Differences (DiD) with a simulation approach using System Dynamics. The empirical approach is used to identify the causal impact of AI adoption on ROA, NPLs, and LDR through econometric modelling, while the System Dynamics approach models' dynamic interactions and long-term feedback arising from AI investment, including potential performance declines in the early stages of implementation. The integration of these two approaches produces an analytical framework that combines causal econometrics with an understanding of systemic dynamics. Thus, this study not only enriches the empirical literature on the relationship between AI adoption and banking performance in Indonesia but also produces more robust and reliable findings through an integrated methodological approach. The findings are expected to provide strong, evidence-based policy references for stakeholders, particularly Bank Indonesia, to strengthen macroprudential supervision and develop a financial system stability framework, so that AI-driven efficiency can be achieved sustainably and remain aligned with risk management.

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8 Fadi S. Shiyyab et al., "The Impact of Artificial Intelligence Disclosure on Financial Performance," *International Journal of Financial Studies* 11, no. 3 (2023): 115, https://doi:10.3390/ijfs11030115.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Theoretically, the relationship between AI adoption and improved bank performance can be explained through the Resource-Based View (RBV) framework, which posits that competitive advantage and superior organisational performance stem from ownership of and the ability to manage strategic resources that are valuable, rare, inimitable, and non-substitutable (VRIN).[9] In the banking context, AI capabilities can be viewed as strategic resources due to their ability to improve operational efficiency, enhance decision-making accuracy, strengthen risk management, and improve the quality of personalised services. Strategic resources enable banks to improve operational efficiency and financial performance on an ongoing basis.[10] AI is also a key driver of digital transformation in the financial sector, leveraging data analytics, machine learning, and predictive modelling for asset allocation and risk management.[11]

In much of the previous banking literature, ROA is widely used as a key indicator of profitability because it reflects a bank's ability to manage its assets efficiently.[12] With the increasing digitisation of the financial sector, research attention has begun to focus on the role of AI in influencing this performance. A number of empirical studies show that AI adoption is positively correlated with an increase in ROA. According to Gupta et al., AI can support human resource management through automation, employee development, and workforce planning, thereby contributing to improved employee and operational performance.[13] These findings are consistent with other studies showing that AI implementation can improve a company's financial performance through more effective asset management.[14] More specific evidence in the banking

[9] Jay B. Barney, "Firm Resources and Sustained Competitive Advantage," *Journal of Management* 17, no. 1 (1991): 105–111, https://doi.org/10.1177/014920639101700108.

[10] Mahfuzur Rahman et al., "Adoption of Artificial Intelligence in Banking Services: An Empirical Analysis," *International Journal of Emerging Markets* 18, no. 10 (2021): 4289–4290, https://doi.org/10.1108/IJOEM-06-2020-0724.

[11] Claudio Scardovi, "Transformation in Risk Management," chap. 9 in *Digital Transformation in Financial Services* (Springer, 2017), 143–144, https://doi.org/10.1007/978-3-319-56947-5_9.

[12] Saeed Sazzad Jeris, "Factors Influencing Bank Profitability in a Developing Economy," *International Journal of Asian Business and Information Management* 12, no. 3 (2021): 336, https://doi:10.4018/ijabim.20210701.oa20.

[13] Priyanka Gupta, Girish Lakhera, and Manu Sharma, "Examining the Impact of Artificial Intelligence on Employee Performance in the Digital Era: An Analysis and Future Research Direction," The Journal of High Technology Management Research 35, no. 2 (2024): 2–4, 100520, https://doi.org/10.1016/j.hitech.2024.100520

[14] Yu Li et al., "Artificial Intelligence, Dynamic Capabilities, and Corporate Financial Asset Allocation," *International Review of Financial Analysis* 96 (2024): 10, https://doi:10.1016/j.irfa.2024.103773.; Tania Babina, Anastassia Fedyk, Alex He, and James Hodson, "Artificial Intelligence, Firm Growth, and Product Innovation," *Journal of Financial Economics* 151 (2024): 5, 103745, https://doi.org/10.1016/j.jfineco.2023.103745.

sector is provided by Shiyyab et al., who analysed banks on the Amman Stock Exchange and found that AI adoption significantly increased ROA and ROE,[15] and by Li, who highlighted the role of AI adoption strategy in increasing profitability and operational efficiency.[16]

However, previous literature also shows that the impact of technology on ROA is not always linear. Aguegboh, Agu, and Nnetu-Okolieuwa, in a cross-sectional study of 35 countries in Sub-Saharan Africa, found that the adoption of information and communication technology (ICT) was negatively correlated with ROA, despite having a positive impact on other performance indicators.[17] These findings indicate that the benefits of technology are greatly influenced by institutional readiness, cost structures, and the level of implementation maturity. These empirical differences underscore the importance of a theoretical framework that explains the mechanisms by which technology translates into improved performance. In this context, the concept of dynamic capabilities is relevant for explaining how AI enables banks to continuously reconfigure their resources and operational processes in response to environmental changes, ultimately reflected in improved ROA.[18] Based on a review of these studies, the first hypothesis is formulated as follows:

H1: Ceteris paribus, banks that adopt AI technology have higher ROA.

In terms of profitability, the implications of AI adoption for credit risk management are a significant issue in banking. Although most previous studies have focused on profitability, AI has the potential to play a fundamental role in reducing credit risk. AI and machine learning technologies can improve credit assessment accuracy by processing large datasets and incorporating multiple predictive variables, thereby enhancing default prediction and strengthening credit risk analysis and controls.[19] In the aggregate, these mechanisms can reduce the level of non-performing loans and improve the efficiency of banking risk management.[20] Fujii et al. demonstrate that contextual AI-based methods can

[15] Shiyyab et al., "The Impact of Artificial Intelligence Disclosure," 16.

[16] Zhen Li, "Does Artificial Intelligence Enhance Bank Profitability? Evidence from China," Finance Research Letters 90 (2026): 7, https://doi.org/10.1016/j.frl.2025.109366.

[17] Aguegboh et al., "ICT Adoption," 414–417.

[18] David J. Teece et al., "Dynamic Capabilities and Strategic Management," *Strategic Management Journal* 18, no. 7 (1997): 526, https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z.

[19] Flavio Barboza, Herbert Kimura, and Edward Altman, "Machine Learning Models and Bankruptcy Prediction," *Expert Systems with Applications* 83 (2017): 405–406, https://doi.org/10.1016/j.eswa.2017.04.006

[20] Martin Leo et al., "Machine Learning in Banking Risk Management: A Literature Review," *Risks* 7, no. 1 (2019): 29, https://doi:10.3390/risks7010029.

improve the extraction and classification of risk-related information compared with simpler pattern-matching approaches.[21]

These implications can be explained through the theory of information asymmetry, which emphasises that the information gap between banks and debtors is the main source of default risk.[22] By utilising AI, banks can reduce information asymmetry through more comprehensive and accurate data analysis, thereby improving the quality of credit assessments. In previous banking literature, credit risk is generally measured using the NPL ratio.[23] Although AI is often conceptualised as capable of reducing NPL, empirical evidence in the Indonesian banking sector remains limited. Therefore, the second hypothesis is formulated as follows:

H2: Ceteris paribus, banks that adopt AI technology have lower NPL ratios.

Furthermore, the adoption of AI has the potential to affect banking intermediation functions, particularly the balance between lending and fundraising. Digital technology, in this case AI, can improve the efficiency of banking intermediation.[24] These improvements are directly related to the stability of bank liquidity, which is generally measured by the LDR. Digital technology, including AI, has been proven to improve the efficiency of banking intermediation by reducing transaction costs and increasing the speed and accuracy of asset and liability management.[25] This increase in efficiency is closely related to the stability of bank liquidity, which is generally measured by the LDR. In this context, the adoption of AI enables banks to manage liquidity more optimally, thereby supporting the balance of intermediation functions. Thus, the third hypothesis is formulated as follows:

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21 Motomasa Fujii et al., "Extraction and Classification of Risk-Related Sentences from Securities Reports," *International Journal of Information Management Data Insights* 2, no. 2 (2022): 1–2, 100096, https://doi.org/10.1016/j.jjimei.2022.100096.

22 Joseph E. Stiglitz and Andrew Weiss, "Credit Rationing in Markets with Imperfect Information," *The American Economic Review* 71, no. 3 (1981): 403, https://www.jstor.org/stable/1802787.

23 Maryem Naili and Younès Lahrichi, "Banks' Credit Risk, Systematic Determinants and Specific Factors: Recent Evidence from Emerging Markets," *Heliyon* 8, no. 2 (2022): 5, https://doi:10.1016/j.heliyon.2022.e08960.

24 Rahman et al., "Adoption of Artificial Intelligence in Banking Services," 4271–72.

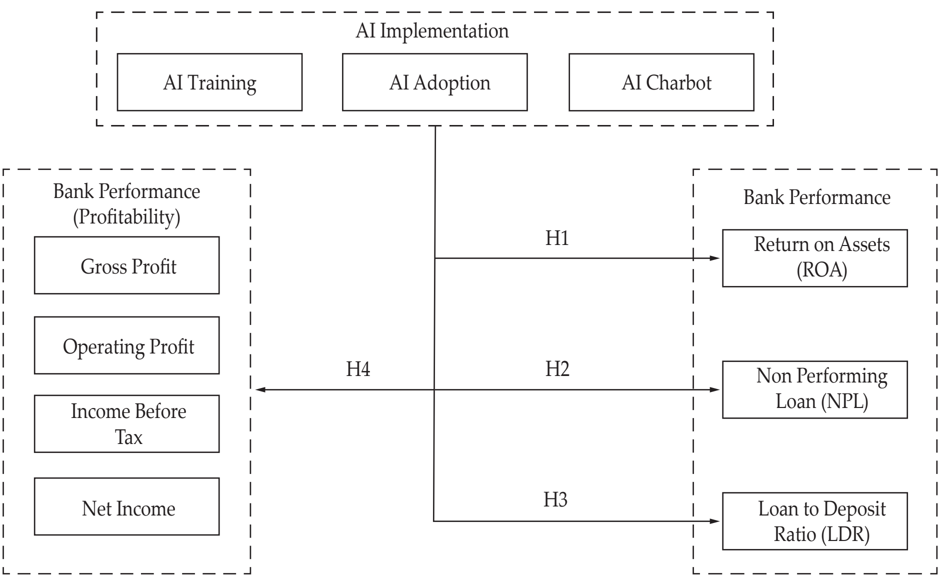
25 Allen N. Berger, "The Economic Effects of Technological Progress: Evidence from the Banking Industry," *Journal of Money, Credit and Banking* 35, no. 2 (2003): 149–150.; Thorsten Beck et al., "Financial Innovation: The Bright and the Dark Sides," *Journal of Banking & Finance* 72 (2016): 29–30, https://doi.org/10.1016/j.jbankfin.2016.06.012; Florian Königstorfer and Stefan Thalmann, "Applications of Artificial Intelligence in Commercial Banks: A Research Agenda for Behavioral Finance," *Journal of Behavioral and Experimental Finance* 27 (2020): 12, https://doi.org/10.1016/j.jbef.2020.100352.

H3: Ceteris paribus, banks that adopt AI technology have a lower LDR.

To capture the impact of AI on banking performance more comprehensively, the analysis requires not only an empirical approach but also one capable of representing the dynamic interactions among variables. The System Dynamics (SD) approach offers a simulation-based framework for mapping feedback mechanisms and structural relationships within the system.[26] Although prior literature demonstrates the potential of AI to improve financial performance, banking studies examining the impact of AI using the SD approach remain limited. Therefore, this study combines regression analysis and simulation to assess the impact of AI more comprehensively, leading to the fourth hypothesis:

H4: Ceteris paribus, according to a System Dynamics simulation, the application of AI technology can increase bank profitability.

Figure 1.
Conceptual Framework



Source: Author's analysis

Although international literature shows the positive impact of AI on ROA, NPL, and LDR, empirical evidence specifically examining this relationship in the context of Indonesian banking remains very limited. Most studies are cross-

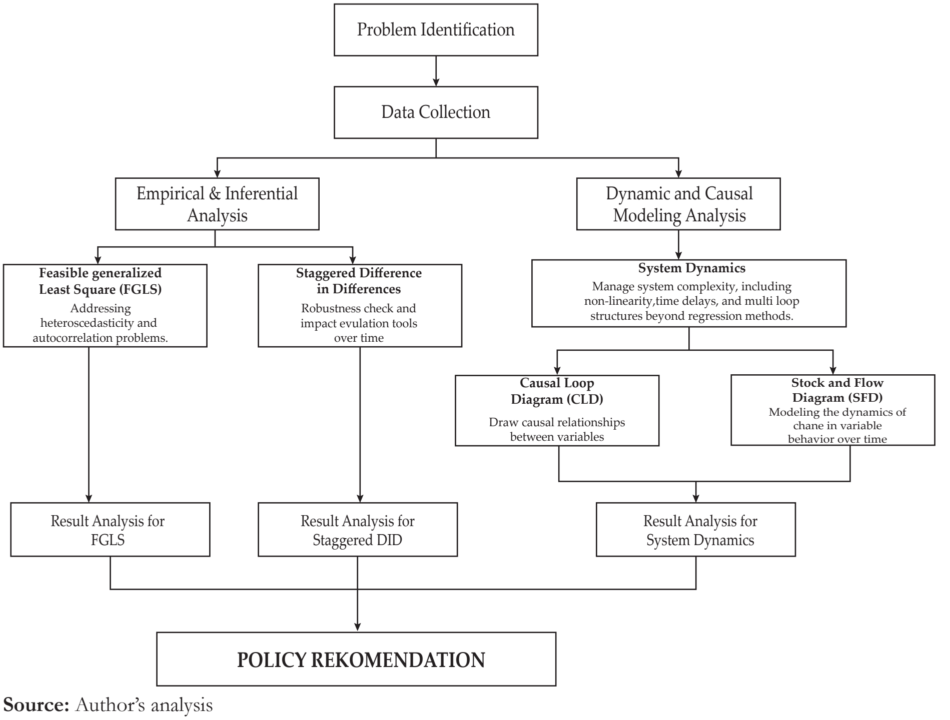
[26] Stefano Armenia et al., "Zooming in and out the Landscape: Artificial Intelligence and System Dynamics in Business and Management," *Technological Forecasting and Social Change* 200 (2024): 3, 123131, https://doi.org/10.1016/j.techfore.2023.123131

country or focus on regions outside Indonesia, so they do not fully capture the institutional characteristics and level of maturity of AI adoption in the national banking sector. This study aims to fill this gap by providing Indonesia-based empirical evidence through an empirical and simulation approach.

III. DATA AND METHODOLOGY

This research integrates FGLS with Driscoll-Kraay robustness checks and Staggered DiD for empirical analysis, and SD Modelling for dynamic and causal analysis. These methods complement each other, enhancing the robustness of the results. SD modelling is applied in two phases: conceptualisation (problem articulation and policy design) and simulation (policy formulation, testing, and analysis).[27] Combining regression and system dynamics improves prediction accuracy and deepens analysis of financial systems, as demonstrated in previous studies.[28]

Figure 2.
Flow of Research



Source: Author's analysis

[27] Mohammadreza Zolfagharian et al., "Combining System Dynamics Modeling with Other Methods: A Systematic Review," in the *Proceedings of the 59th Annual Meeting of the International Society for the Systems Sciences* 1, no. 1 (2015): 2-4.

[28] Witsanuchai Srijariya et al., "System Dynamic Modeling: An Alternative Method for Budgeting," *Value in Health* 11 (2008): S117, https://doi:10.1111/j.1524-4733.2008.00375.x.

III.A. FGLS and robustness checking with Driscoll-Kraay Standard Error

To analyse the impact of AI adoption on banking performance, this study utilises a panel dataset of 50 banks in Indonesia, covering monthly data from 2017 to 2023, for a total of 84 periods. Therefore, the total panel dataset is 4200 observations. The list and description of the banks are explained in Appendix 1. The dependent variables are ROA, NPLs, and LDR. These three indicators are commonly used due to:

1. ROA reflects a firm's ability to generate returns from its asset base and serves as an indicator of financial performance and asset value creation;[29]
2. NPL measures the proportion of bad loans in a bank's portfolio. High NPL ratios indicate solvency risks, affecting profitability and financial stability;[30]
3. LDR measures a bank's liquidity by comparing its loans to total deposits. A balanced LDR ensures banks maintain liquidity while maximising loan issuance.[31]

The independent variables are dummy variables for AI adoption, AI chatbot, and AI training, which are set to 1 if banks adopt AI, use a chatbot, or hold/join training for their employees, respectively, and 0 otherwise. We determined the starting dates of AI adoption, AI chatbot adoption, and AI training for each bank by reviewing their annual reports and Indonesian news sources. If they explained the plan for using AI, we treated the stated date as a dummy variable. The construction of dummy variables for AI adoption, chatbot implementation, and training, based on annual reports and news articles, introduces potential measurement error, as these sources may not accurately reflect the timing, scale, or effectiveness of actual AI integration within banks. Announcements may precede operational deployment, implementation may be partial or phased, or initiatives may be discontinued without public disclosure, leading to misclassification. Such non-differential measurement error typically attenuates estimated coefficients toward zero in regression models, reducing the observed magnitude of AI's impact. However, if misclassification is systematic, for example, if banks with stronger performance are more likely to report AI initiatives, estimates may be biased upward, overstating AI's benefits. In staggered DiD designs, timing inaccuracies further violate the no-anticipation assumption and distort dynamic treatment-effect estimates,

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[29] Icuk Rangga Bawono and Rangga Handika, "How Do Accounting Records Affect Corporate Financial Performance? Empirical Evidence from the Indonesian Public Listed Companies," *Heliyon* 9, no. 4 (2023): 2, https://doi.org/10.1016/j.heliyon.2023.e14950.

[30] Markus Schulte and Adalbert Winkler, "Drivers of Solvency Risk – Are Microfinance Institutions Different?" *Journal of Banking & Finance* 106 (2019): 414, https://doi.org/10.1016/j.jbankfin.2019.07.009.

[31] Luca Bellardini, Pierluigi Murro, and Daniele Previtali, "Measuring the Risk Appetite of Bank-Controlling Shareholders: The Risk-Weighted Ownership Index," *Global Finance Journal* 60 (2024): 2–3, 100935, https://doi.org/10.1016/j.gfj.2024.100935.

complicating causal interpretation. The definition of variables, data sources, and abbreviations are provided in Table 1.

Table 1.
The variables abbreviation, definition, and Sources

Variables	Abbr.	Definition	Sources
Dependent variables			
Return on Asset	ROA	Measures how effectively a company converts its investment in assets into net income	OJK
Non-performing Loan	NPL	Measures a bank's ability to cover loan withdrawals and meet liquidity needs	OJK
Loan to Deposit Ratio	LDR	Indicates the quality of a bank's credit management.	OJK
Independent variables			
AI Adoption	AI_adoption	*Dummy variable* for banks that first time utilises AI (e.g., fraud detection, service, recruitment, and others) and continually use it	Articles and Bank Annual Reports
AI Chatbot	AI_chatbot	*Dummy variable* for banks that first time utilises AI chatbot or virtual assistant and continually use it	Articles and Bank Annual Reports
AI Training	AI_training	*Dummy variable* for banks that held/join AI training/webinar for the employees at time t	Articles and Bank Annual Reports
Control Variables			
Capital Adequacy Ratio	CAR	The ratio of a bank's capital in relation to its risk weighted assets and current liabilities (%)	OJK
Credit inclusion	INK	The proportion of credit access by society (%) $INK = \frac{Customer\ fund\ account\ +\ MSMEs\ account}{Adult\ Population}$	OJK
Deposit interest rates	SB_DEP	The rate of interest that a financial institution pays on cash deposits (&)	OJK
Loan demand	Loandemand	The proportion of loan demand (%) $Loandemand = GDPRiil100 * \frac{Credit\ P3}{Credit\ SPI}$	OJK
GDP Real	GDPRiil100	GDP Real growth in Indonesia (%)	BPS

Tables 2 and 3, respectively, show the results of the Variance Inflation Factor (VIF) and correlation matrix for the variables used. The rule of thumb for VIF < 5.00[32] shows that there is no collinearity among the variables used in this study. Also, the correlation matrix in Table 3 shows that there is no high linear correlation among variables (<0.5), which means there is low multicollinearity. However, AI_adoptionion and AI_chatbot are highly

[32] Robert M. O'brien, "A Caution Regarding Rules of Thumb for Variance Inflation Factors," *Quality & Quantity* 41, no. 5 (2007): 684, https://link.springer.com/article/10.1007/s11135-006-9018-6.

correlated with a 0.718 coefficient. Therefore, for convenience, this study does not include independent variables in the same model.

Table 2.
Multicollinearity test with Variance Inflation Factor (VIF)

	A	B	C	D	E	F	G	H
VIF	2.39	2.35	1.01	1.96	1.13	2.10	1.34	1.42
1/VIF	0.42	0.43	0.99	0.51	0.87	0.47	0.74	0.70
Mean VIF	**1.71**							

Notes: A = AI_adoptionion; B = AI_chatbot; C = AI_training; D = CAR; E = INK; F = SB_DEP G = Loandemand; H = GDPRiil100

Table 3.
Multicollinearity test with Correlation matrix

	A	B	C	D	E	F	G	H
A	1.000							
B	0.718	1.000						
C	0.053	0.078	1.000					
D	-0.044	-0.108	-0.018	1.000				
E	0.154	0.230	0.017	-0.102	1.000			
F	-0.307	-0.295	-0.26	-0.199	-0.136	1.000		
G	0.136	0.188	0.031	0.055	0.296	-0.095	1.000	
H	-0.008	0.013	0.002	0.021	0.002	-0.060	0.416	1.000

Notes: A = AI_adoption; B = AI_chatbot; C = AI_training; D = CAR; E = INK; F = SB_DEP; G = Loandemand; H = GDPRiil100

To thoroughly examine the impact of AI on banks' financial performance, we employ a linear model with the FGLS method. Feasible Generalised Least Squares (FGLS) is an econometric estimation method by Greene[33] used for panel data when the standard assumptions of Ordinary Least Squares (OLS) are violated due to AR(1) autocorrelation within panels, cross-sectional correlation across panels, and heteroskedasticity across panels. In an ideal scenario, Generalised Least Squares (GLS) provides more efficient estimates than OLS by transforming the model using the inverse of the variance-covariance matrix of the error terms, Ω. However, in practical applications, Ω is rarely known and must be estimated. FGLS is a two-step procedure in which an initial estimate of Ω is obtained, and this estimated matrix is then used to transform the model for final estimation.

The use of FGLS requires several conditions to be met. First, there should be clear evidence of heteroscedasticity or autocorrelation in the error terms, which makes OLS inefficient and potentially biased in hypothesis testing.

[33] William H. Greene, *Econometric Analysis*, 8th ed. (Harlow: Pearson, 2018), 349–350.

Second, it is crucial to have a consistent estimator of Ω. Third, to ensure the estimator's accuracy, the number of time periods should exceed the number of cross-sectional units in panel data (T > N).[34]

The analysis begins with preliminary examinations to assess cross-sectional dependence (CSD), slope heterogeneity (SH), heteroscedasticity, and serial correlation before applying FGLS. First, the CSD test follows Pesaran[35] to identify interdependence among cross-sectional units, crucial in panel studies where economic interdependence can cause spillover effects[36]. Heteroscedasticity is examined using the Breusch-Pagan test[5], as non-constant error variance affects statistical inference.[37] Serial correlation is detected to ensure that residuals are not correlated over time to prevent biased estimates.[38] Based on the FGLS method, the equations this study uses are as follows:

$$ROA_{it} = \beta_0 + \beta_1 Ai_a doption_{it} + \sum_{m=2}^{6} \beta_m \, Control\, Variable_{it} + \varepsilon_{it} \quad \text{(Model 1)}$$

$$ROA_{it} = \beta_0 + \beta_1 Ai_c hatbot_{it} + \sum_{m=2}^{6} \beta_m \, Control\, Variable_{it} + \varepsilon_{it} \quad \text{(Model 2)}$$

$$ROA_{it} = \beta_0 + \beta_1 Ai_t raining_{it} + \sum_{m=2}^{6} \beta_m \, Control\, Variable_{it} + \varepsilon_{it} \quad \text{(Model 3)}$$

$$NPL_{it} = \beta_0 + \beta_1 Ai_a doption_{it} + \sum_{m=2}^{6} \beta_m \, Control\, Variable_{it} + \varepsilon_{it} \quad \text{(Model 4)}$$

$$NPL_{it} = \beta_0 + \beta_1 Ai_c hatbot_{it} + \sum_{m=2}^{6} \beta_m \, Control\, Variable_{it} + \varepsilon_{it} \quad \text{(Model 5)}$$

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[34] Mantobaye Moundigbaye et al., "Which Panel Data Estimator Should I Use?: A Corrigendum and Extension," *Economics: The Open-Access, Open-Assessment E-Journal*, (2018): 28, https://doi.org/10.5018/economics-ejournal.ja.2018-4.

[35] M. Hashem Pesaran, "General Diagnostic Tests for Cross Section Dependence in Panels" (working paper, Faculty of Economics, University of Cambridge, 2004), 5-8, https://doi.org/10.17863/CAM.5113.; M. Hashem Pesaran, "Testing Weak Cross-Sectional Dependence in Large Panels," *Econometric Reviews* 34, no. 6-10 (2014): 1094–1096, https://doi.org/10.1080/07474938.2014.956623.

[36] M. Hashem Pesaran. "Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure." *Econometrica* 74, no. 4 (2006): 970, https://doi.org/10.1111/j.1468-0262.2006.00692.x; M. Hashem Pesaran, "A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence," *Journal of Applied Econometrics* 22, no. 2 (2007): 267, https://doi.org/10.1002/jae.951.; Bright Akwasi Gyamfi et al., "An Investigation into the Anthropogenic Effect of Biomass Energy Utilization and Economic Sustainability on Environmental Degradation in E7 Economies," *Biofuels, Bioproducts and Biorefining* 15, no. 3 (2021): 844–845, https://doi.org/10.1002/bbb.2206.

[37] Jeffrey M. Wooldridge, "Heteroskedasticity," chap. 8 in *Introductory Econometrics: A Modern Approach* (Cengage Learning, 2013), 277.

[38] Benjamin Born and Jörg Breitung, "Testing for Serial Correlation in Fixed-Effects Panel Data Models," *Econometric Reviews* 35, no. 7 (2016): 1290–1291, https://doi.org/10.1080/07474938.2014.976524.

$$NPL_{it} = \beta_0 + \beta_1 Ai_t raining_{it} + \sum_{m=2}^{6} \beta_m \, Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 6)}$$

$$LDR_{it} = \beta_0 + \beta_1 Ai_a doption_{it} + \sum_{m=2}^{6} \beta_m \, Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 7)}$$

$$LDR_{it} = \beta_0 + \beta_1 Ai_c hatbot_{it} + \sum_{m=2}^{6} \beta_m \, Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 8)}$$

$$LDR_{it} = \beta_0 + \beta_1 Ai_t raining_{it} + \sum_{m=2}^{6} \beta_m \, Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 9)}$$

To complement the baseline FGLS estimates and verify that the sign and significance of key coefficients are not driven by specific assumptions about error structures, we conduct a robustness check using a fixed-effects (FE) panel estimator with Driscoll–Kraay standard errors. This method is particularly suitable for panels with cross-sectional dependence and heteroskedasticity, and it remains consistent in the presence of general forms of serial correlation and spatial dependence. Unlike FGLS, which imposes a parametric structure on the covariance matrix, the Driscoll–Kraay approach applies a nonparametric variance–covariance estimator that is robust to very general forms of cross-section and time dependence. The results confirm that the positive effects of AI adoption and AI chatbots on ROA, as well as the negative effects on NPL and LDR, remain statistically significant under this alternative specification, thereby reinforcing the credibility of our main findings against potential artefacts of the FGLS estimation.

III.B. Staggered DiD

After that, to accurately estimate the impact of AI adoption and AI chatbots on banks' financial performance, this study uses a staggered DiD method as proposed by Callaway and Sant'Anna.[39]

Staggered DiD is designed to analyse causal effects when treatment is introduced at different points in time across different groups. Unlike the standard two-period, two-group DiD, where a single treatment effect is estimated, staggered DiD allows for treatment effect heterogeneity by accounting for dynamic effects over time and across cohorts. One of the key advantages is its ability to incorporate the variation in treatment timing while

[39] Brantly Callaway and Pedro H. C. Sant'Anna, "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics* 225, no. 2 (2021): 200–202, https://doi.org/10.1016/j.jeconom.2020.12.001.

maintaining a DiD approach to causal inference. Instead of assuming that the treatment effect is constant over time, this approach allows us to examine how the impact evolves across different cohorts.

Several core assumptions must be met: (1) the irreversibility of treatment condition states that once a unit receives treatment, it remains treated in all subsequent periods; (2) the parallel trends assumption is crucial for identification; and (3) there is no anticipation effect assumption, which states that units should not change their behaviour in expectation of future treatment. If units anticipate receiving treatment and adjust their actions before treatment is implemented, it can bias the estimated treatment effects. Lastly, we can use either (i) a never-treated group, which consists of units that never receive treatment throughout the study period, or (ii) a not-yet-treated group, which consists of units that have not yet received treatment at a given time but will be treated later.

To estimate the Average Treatment on the Treated (ATET), the general model with cohort-specific effects of the Staggered DiD is:

$$ROA_{it} = \alpha_i + \gamma_t + \sum_{g \in G} \delta_{g,t} D_{i,g,t}^{Ai\ adoption} + \sum_{m=1}^{5} \beta_m\, Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 10)}$$

$$ROA_{it} = \alpha_i + \gamma_t + \sum_{g \in G} \delta_{g,t} D_{i,g,t}^{Ai\ chatbot} + \sum_{m=1}^{5} \beta_m\, Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 11)}$$

$$NPL_{it} = \alpha_i + \gamma_t + \sum_{g \in G} \delta_{g,t} D_{i,g,t}^{Ai\ adoption} + \sum_{m=1}^{5} \beta_m\, Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 12)}$$

$$NPL_{it} = \alpha_i + \gamma_t + \sum_{g \in G} \delta_{g,t} D_{i,g,t}^{Ai\ chatbot} + \sum_{m=1}^{5} \beta_m\, Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 13)}$$

$$LDR_{it} = \alpha_i + \gamma_t + \sum_{g \in G} \delta_{g,t} D_{i,g,t}^{Ai\ adoption} + \sum_{m=1}^{5} \beta_m\, Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 14)}$$

$$LDR_{it} = \alpha_i + \gamma_t + \sum_{g \in G} \delta_{g,t} D_{i,g,t}^{Ai\ chatbot} + \sum_{m=1}^{5} \beta_m\, Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 15)}$$

In these specifications, αi represents Bank fixed effects capturing time-invariant characteristics of each bank, γ_t is time fixed effects, controlling for macroeconomic shocks affecting all banks, $D_{i,g,t}$ is the indicator variable for treatment, equal to 1 if bank i was treated in cohort g and time t is post-treatment; 0 otherwise, and $\delta_{g,t}$ is the treatment effect for each cohort and time period, allowing for heterogeneous effects across cohorts.

To examine how the treatment effect evolves over time (pre- and post-treatment effects), we use an event-study model

$$ROA_{it} = \alpha_i + \gamma_t + \sum_{e=-K}^{L} \delta_e 1\{EventTime_{i,t} = e\} + \sum_{m=1}^{5} \beta_m Control\ Variable_{it} + \varepsilon_{it} \qquad \text{(Model 16)}$$

$$NPL_{it} = \alpha_i + \gamma_t + \sum_{e=-K}^{L} \delta_e 1\{EventTime_{i,t} = e\} + \sum_{m=1}^{5} \beta_m Control\ Variable_{it} + \varepsilon_{it} \qquad \text{(Model 17)}$$

$$LDR_{it} = \alpha_i + \gamma_t + \sum_{e=-K}^{L} \delta_e 1\{EventTime_{i,t} = e\} + \sum_{m=1}^{5} \beta_m Control\ Variable_{it} + \varepsilon_{it} \qquad \text{(Model 18)}$$

where $EventTime_{i,t}=t-g$ represents the time relative to the treatment date g, δ_e represents the treatment effect at different event times e (e.g. $e=0$ for the first period of treatment, $e=-1$ for one period before, etc.), K represents the number of pre-treatment periods included in estimation, and L represents the number of post-treatment periods included in estimation. Lastly, we estimate the average treatment effect for each cohort:

$$ROA_{it} = \alpha_i + \gamma_t + \sum_{g \in G}^{L} \delta_g 1\{Cohort_i = g\} * Ai\ adoption_{it} + \sum_{m=1}^{5} \beta_m Control\ Variable_{it} + \varepsilon_{it} \qquad \text{(Model 19)}$$

$$ROA_{it} = \alpha_i + \gamma_t + \sum_{g \in G}^{L} \delta_g 1\{Cohort_i = g\} * Ai\ chatbot_{it} + \sum_{m=1}^{5} \beta_m Control\ Variable_{it} + \varepsilon_{it} \qquad \text{(Model 20)}$$

$$NPL_{it} = \alpha_i + \gamma_t + \sum_{g \in G}^{L} \delta_g 1\{Cohort_i = g\} * Ai\ adoption_{it} + \sum_{m=1}^{5} \beta_m Control\ Variable_{it} + \varepsilon_{it} \qquad \text{(Model 21)}$$

$$NPL_{it} = \alpha_i + \gamma_t + \sum_{g \in G}^{L} \delta_g 1\{Cohort_i = g\} * Ai\ chatbot_{it} + \sum_{m=1}^{5} \beta_m Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 22)}$$

$$LDR_{it} = \alpha_i + \gamma_t + \sum_{g \in G}^{L} \delta_g 1\{Cohort_i = g\} * Ai\ adoption_{it} + \sum_{m=1}^{5} \beta_m Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 23)}$$

$$LDR_{it} = \alpha_i + \gamma_t + \sum_{g \in G}^{L} \delta_g 1\{Cohort_i = g\} * Ai\ chatbot_{it} + \sum_{m=1}^{5} \beta_m Control\ Variable_{it} + \varepsilon_{it} \quad \text{(Model 24)}$$

III.C. System Dynamics (SD)

This study uses the System Dynamics (SD) approach to simulate the dynamic impact of AI implementation on banking profitability over a 30-month period, comparing two scenarios: banks that adopt AI and banks that do not adopt AI. The SD approach was chosen for its ability to capture feedback mechanisms, nonlinear relationships, multiple interacting loops, simultaneity, and time delays in complex dynamic systems.[40]. This simulation was conducted with monthly time steps, using primary data sourced from Indonesian Banking Statistics (SPI) published by the Financial Services Authority (OJK) for the period November 2021 to October 2024. The data were used to parameterise investment behaviour, income generation, and cost structures in the banking system. The determination of initial values and additional parameters also referred to the findings from global surveys, particularly the McKinsey Global Survey on AI[41] and experimental evidence of productivity gains from the use of generative AI.[42]

Referring to Dell'Acqua et al., AI adoption is assumed to increase labour productivity, while the impact on revenue growth and cost efficiency is conservatively set at five per cent, in line with the results of the McKinsey

[40] Bilash Kanti Bala, Fatimah Mohamed Arshad, and Kusairi Mohd Noh, *System Dynamics: Modelling and Simulation* (Singapore: Springer, 2017), 3–5, 13.

[41] McKinsey & Company, *The State of AI in 2024: Agents, Innovation, and Transformation*, Accessed July 29, 2026, https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai.

[42] Fabrizio Dell'Acqua et al., *Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of Artificial Intelligence on Knowledge Worker Productivity and Quality*, Harvard Business School Working Paper No. 24-013 (September 2023), 12–13, https://doi.org/10.2139/ssrn.4573321.

Global Survey on AI. Banking IT capital expenditure data is obtained by aggregating the IT capital expenditure disclosed by publicly listed banks, including Indonesia's state-owned banks (Himbara) and several other listed banks.

Table 4.
Core Variable Operationalisation in System Dynamics

Submodel	Variable	Type	Definition / Specification
AI in Finance	AI in Finance	Stock	Level of AI adoption in banking, evolving through reinforcing and balancing mechanisms
	Increasing Factors	Flow	Composite effect of cost reduction, revenue enhancement, and productivity improvement from AI
	Decreasing Factors	Flow	Adjustment and labour-related risks associated with AI adoption
	AI Investment Cost	Converter	Portion of banking IT capital expenditure allocated to AI investment
Gross Profit	Gross Profit	Stock	Accumulated difference between financial income and financial expenses
	Financial Income	Flow	Investment returns and AI-induced efficiency gains with implementation delay
	Financial Expenses	Flow	Operational and catchment-related costs
Operating Profit	Operating Profit	Stock	Net operating performance after administrative income and expenses
	Administrative Income	Flow	Income affected by AI investment, aggregate income, and gross profit
	Administrative Expenses	Flow	Operating costs including AI implementation and aggregate expenses
Income Before Tax	Income Before Tax	Stock	Operating profit adjusted for transaction delay
	Transaction Delay	Converter	Time lag between operating profit and taxable income
Net Income	Net Income	Stock	Final profitability after taxation and adjustment delays
	Taxes	Converter	Fixed proportion of income before tax
	Delay Net Income	Converter	Adjustment lag in profit realisation

Source: Author's analysis

The SD model in this study is organised into five interconnected submodels that represent the stages of bank profitability formation: AI adoption in the financial sector, gross profit, operating profit, income before tax, and net profit. AI adoption is modelled as a stock variable that develops through reinforcing effects in the form of increased productivity, increased revenue, and reduced costs, as well as balancing effects that reflect the risks of organisational and workforce adjustments. These dynamics then affect financial income and costs through delayed investment effects, reflecting the gradual realisation of AI benefits.

Financial performance variables are modelled using a stock–flow structure that follows accounting logic, in which gross profit, operating profit, pre-tax income, and net income accumulate over time, driven by inflows and outflows reflecting investment performance, operational efficiency, and tax liabilities. The time delay element is explicitly included to capture adjustment frictions in AI implementation and financial transaction processes. All monetary variables are expressed in trillions of rupiah.

The causal structure and behaviour of the model are represented through Causal Loop Diagrams (CLDs) and Stock and Flow Diagrams (SFDs). The model specifications were developed by adapting and integrating SD models from previous studies, particularly Kumari et al. on AI adoption in the financial sector[43] and Becerra et al. on financial profitability dynamics.[44] The integration of these two frameworks enables this model to coherently represent how AI-based technological changes transmit through banking operations and ultimately affect profitability performance dynamically.

IV. RESULT

IV.A. FGLS and Driscoll-Kraay Estimation

Before proceeding to the regression result, we consider several assumptions. Table 5 presents the results of the Heteroscedasticity, Cross-sectional correlation, and Cross-sectional dependence tests for the model used in this study. These tests reveal statistical significance at the 1% level, indicating the presence of heteroscedasticity, Cross-sectional correlation and dependence, and serial correlation within the model. Therefore, FGLS will be used for the model specified before.

[43] Bharti Kumari et al., "System Dynamics Approach for Adoption of Artificial Intelligence in Finance," in *Lecture Notes in Mechanical Engineering* (2021): 557, https://doi.org/10.1007/978-981-15-8025-3_54.

[44] Mauricio Becerra-Fernandez, Milton M. Herrera, and Efrain Morales Correa, "Financial Profitability Model Using System Dynamics," in *Proceedings of the XII Encuentro Colombiano de Dinámica de Sistemas* (Bogotá D.C., Colombia, August 2014), 1–2.

Table 5.
Heteroscedasticity, Cross-sectional Correlation and Dependence, and Serial Correlation Test

Test	Statistics (Chi-square)	P-value
Breusch-Pagan LM test for cross-sectional correlation	**11454.644**	**0.000**
Modified Wald statistic for groupwise heteroskedasticity	**1.8e+05**	**0.000**
Bias-corrected Lagrange multiplier-based test for panel serial correlation	**11.85**	**0.001**
CD-test for cross-sectional dependence (Pesaran, 2004/2015)		
• ROA	33.78	0.000
• NPL	15.88	0.000
• LDR	94.38	0.000
• AI_adoptionion	7.85	0.000
• AI_chatbot	3.90	0.000
• AI_training	0.42	0.676
• CAR	110.83	0.000
• INK	11.68	0.000
• SB_DEP	297.78	0.000
• Loandemand	301.26	0.000
• GDPRiil100	320.78	0.000

Source: Author's analysis

Tables 6, 7, and 8 show the estimation results for the ROA, NPL, and LDR variables, respectively. First, in Table 6, the coefficients for AI_adoptionion, AI_chatbot, and AI_training on ROA indicate the impact of these AI initiatives on banks' profitability. Specifically, AI_adoptionion has a significant positive effect on ROA at the 1% level, with a coefficient of 0.116. This implies that banks adopting AI have an ROA that is 0.116 higher than banks that do not adopt AI, holding other factors constant. AI_chatbot also positively impacts ROA with a coefficient of 0.189, significant at the 5% level, suggesting that the integration of AI-powered chatbots improves ROA by 0.189. Similarly, AI_training has a significant negative coefficient (-0.035), indicating that banks emphasising AI training experience a 0.035 lower ROA compared to those that do not.

Table 6.
FGLS Estimation Result for ROA Variables

Variables	Model 1		Model 2		Model 3	
	ROA	ROA	ROA	ROA	ROA	ROA
AI_adoptionion	0.116***	0.08***				
	(0.022)	(0.022)				
AI_chatbot			0.189***	0.231***		
			(0.024)	(0.024)		
AI_training					-0.035***	-0.038***
					(0.012)	(0.013)
CAR		-0.005***		-0.005***		-0.005***
		(0.000)		(0.000)		(0.000)
INK		4.273***		3.942***		4.870***
		(0.893)		(1.05)		(0.864)
SB_DEP_RP		-0.023***		-0.019**		-0.034***
		(0.008)		(0.008)		(0.008)
Loandemand		-0.04		-0.041		-0.035
		(0.032)		(0.032)		(0.032)
GDPRiil100		0.001		0.001		0.001
		(0.002)		(0.002)		(0.002)
_cons	1.543***	1.811***	1.473***	1.731***	1.562***	1.887***
	(0.025)	(0.054)	(0.024)	(0.053)	(0.017)	(0.05)
Observations	4200	4200	4200	4200	4200	4200

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
Source: Author's analysis

Secondly, in Table 7, for the NPL variable, AI_adoptionion has a significant negative coefficient (-0.065) at the 1% level, implying that banks adopting AI have a 0.065 lower NPL ratio than those that do not. This suggests that AI adoption helps banks better manage credit risk, possibly through enhanced predictive analytics and risk assessment models. Similarly, AI_chatbot shows a negative coefficient of -0.072, significant at the 5% level, indicating that AI chatbots contribute to a 0.072 reduction in NPL, potentially by improving customer engagement and loan repayment reminders. On the other hand, AI_training has no significant effect on NPL, as its coefficient is not statistically significant.

Table 7.
FGLS Estimation Result for NPL Variable

Variables	Model 4		Model 5		Model 6	
	NPL	NPL	NPL	NPL	NPL	NPL
AI_adoptionion	-0.068**	-0.071**				
	(0.031)	(0.031)				
AI_chatbot			-0.072**	-0.072**		
			(0.03)	(0.03)		
AI_training					-0.013	-0.015
					(0.016)	(0.016)
CAR		-0.002***		-0.002***		-0.002***
		(0.000)		(0.000)		(0.000)
INK		-1.915**		-1.856**		-1.888**
		(0.9)		(0.897)		(0.924)
SB_DEP_RP		0.008		0.008		0.011
		(0.008)		(0.008)		(0.008)
Loandemand		0.058***		0.058***		0.057***
		(0.02)		(0.02)		(0.02)
GDPRiil100		-0.002*		-0.002*		-0.002*
		(0.001)		(0.001)		(0.001)
_cons	2.865***	2.902***	2.864***	2.902***	2.849***	2.868***
	(0.045)	(0.065)	(0.045)	(0.065)	(.045)	(0.067)
Observations	4200	4200	4200	4200	4200	4200

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
Source: Author's analysis

Lastly, in Table 8 for the LDR variable, AI_adoptionion exhibits a significant negative coefficient (-1.832) at the 1% level, implying that banks adopting AI have a 1.832 lower LDR than those not adopting AI. This could indicate that AI adoption enhances liquidity management, balancing loan disbursements and deposits. AI_chatbot also has a significant negative impact, with a coefficient of -3.178, suggesting a 3.178 lower LDR for banks utilising chatbots. This could reflect improved operational efficiency in deposit mobilisation or a conservative lending approach. Finally, AI_training shows a statistically significant negative coefficient (-5.894), indicating that banks investing in AI training have a 5.894 lower LDR, possibly reflecting strategic adjustments during the implementation phase of AI initiatives.

Table 8.
FGLS Estimation Result for LDR Variable

Variables	Model 7		Model 8		Model 9	
	LDR	LDR	LDR	LDR	LDR	LDR
AI_adoptionion	-1.832***	-4.804***				
	(0.377)	(0.4)				
AI_chatbot			-3.178***	-5.894***		
			(0.418)	(0.435)		
AI_training					-0.363**	-0.653***
					(0.185)	(0.209)
CAR		0.133***		0.133***		0.138***
		(0.011)		(0.012)		(0.012)
INK		-25.61***		-25.01***		-58.198***
		(7.686)		(7.143)		(7.25)
SB_DEP_RP		-0.661***		-0.73***		-0.037
		(0.182)		(0.186)		(0.169)
Loandemand		-0.478		-0.421		-0.759***
		(0.318)		(0.342)		(0.288)
GDPRiil100		0.081**		0.085**		0.085**
		(0.033)		(0.034)		(0.034)
_cons	98.444***	95.792***	98.048***	96.104***	99.249***	91.258***
	(0.902)	(1.248)	(0.868)	(1.283)	(0.796)	(1.155)
Observations	4200	4200	4200	4200	4200	4200

Standard errors are in parentheses
**** $p<.01$, ** $p<.05$, * $p<.1$*

Source: Author's analysis

The robustness check using fixed effects estimation with Driscoll–Kraay standard errors confirm the consistency and reliability of the core findings from the FGLS models. As detailed in Appendices 2–4, the direction and statistical significance of the key coefficients—AI adoption and AI chatbots positively affecting ROA while reducing NPLs and LDR—remain unchanged under this alternative estimation strategy. This consistency across estimators indicates that the reported effects are not artefacts of the specific FGLS assumptions regarding heteroskedasticity, autocorrelation, or cross-sectional correlation. Instead, the results withstand a more flexible and robust treatment of error dependence, reinforcing the empirical credibility of the conclusion that AI adoption meaningfully enhances bank performance and stability in Indonesia.

The use of Driscoll–Kraay standard errors, which are robust to general forms of cross-sectional dependence and serial correlation, addresses potential concerns about unobserved common shocks or spatial linkages among Indonesian banks. The stability of the coefficient signs and significance levels across both estimation approaches underscores the structural nature of the relationship between AI performance and the model specification, rather than a statistical artefact driven by model specification. This methodological reinforcement strengthens the policy relevance of the findings, providing regulators and practitioners with greater confidence in the evidence that AI adoption can contribute positively to profitability, credit risk management, and liquidity efficiency in the banking sector.

IV.B. Staggered Difference-in-Differences

Table 9 below shows the overall ATET result from Staggered DiD. It indicates that AI chatbot implementation significantly increases the LDR by 27.869 (Model 15), suggesting that chatbots enhance operational efficiency and potentially drive higher loan activity relative to deposits. However, for other outcomes, such as ROA and NPL, the effects of both AI adoption and AI chatbots are not statistically significant, indicating no conclusive impact on these metrics. Overall, the findings highlight the targeted influence of AI chatbots on LDR, while their broader financial impacts remain unclear.

Table 9.
ATET result

	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
	ROA	ROA	NPL	NPL	LDR	LDR
AI_adoptionion (1 vs 0)	-0.033		0.686		4.123	
AI_chatbot (1 vs 0)		-0.458		0.667		27.869*

Source: Author's analysis

To facilitate differentiation of ATET results by cohort, Table 10 below presents the estimation results. The results reveal interesting temporal dynamics in the effects of AI adoption and AI chatbot implementation on ROA, NPLs, and LDR, indicating shifts from positive to negative, from negative to positive, or changes in significance over time.

The results reveal that AI's impact on ROA, NPLs, and LDR fluctuates over time. For ROA, AI adoption initially increases profitability in 2018m1, but this effect turns negative in 2019m8 and 2020m7, likely due to transitional costs or operational challenges. However, by 2023m8, ROA improves again, suggesting that organisations adapt to and eventually benefit from AI. For NPL, AI adoption significantly reduces bad loans in 2018m3, indicating better credit management, but in 2020m2, it unexpectedly increases NPL, possibly due to implementation challenges or disruptions in lending practices. By 2023m8, NPLs decline again, implying that banks have refined their AI-driven risk management. For LDR, AI chatbot implementation consistently enhances financial intermediation, with significant increases in 2017m6 and 2018m3, though its significance varies over time, particularly in 2023m2, likely due to external market conditions.

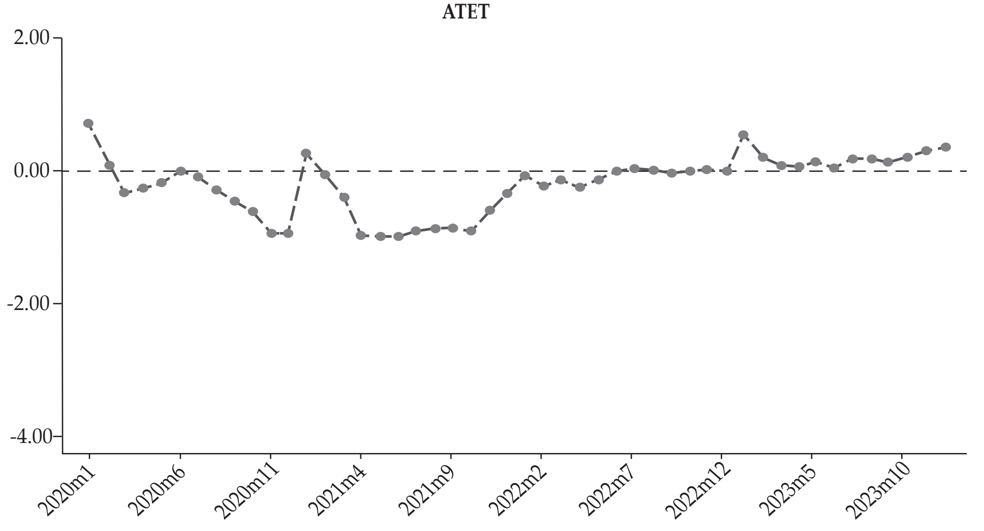
Table 10.
ATET for Each Cohort from the Model Estimated

	ROA		NPL		LDR	
	AI_ adoptionion	**AI_ chatbot**	**AI_ adoptionion**	**AI_ chatbot**	**AI_ adoptionion**	**AI_ chatbot**
Cohort	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
2017m6	0.173	0.180	-0.747	-0.75	19.909	35.469*
2018m1	0.658***		0.098		-11.869***	
2018m3	0.601	-0.913	-1.626***	-1.666*	18.998	40.696*
2019m8	-1.30***		0.044		-1.786	
2019m12	-1.658		-2.096		-160.93***	
2020m2	-0.608		1.139***		-6.313	
2020m3	-0.188	-0.378	0.357	0.457	10.376**	18.919**
2020m7	-0.536***	-0.379***	0.314	0.481	14.213*	25.227*
2021m3		-0.348		0.198		-8.385*
2022m4		-0.707**		-0.237		15.585*
2023m2		-0.189		-0.092		5.096
2023m8	0.515***	0.506***	-0.366***	-0.356***	1.704	1.394

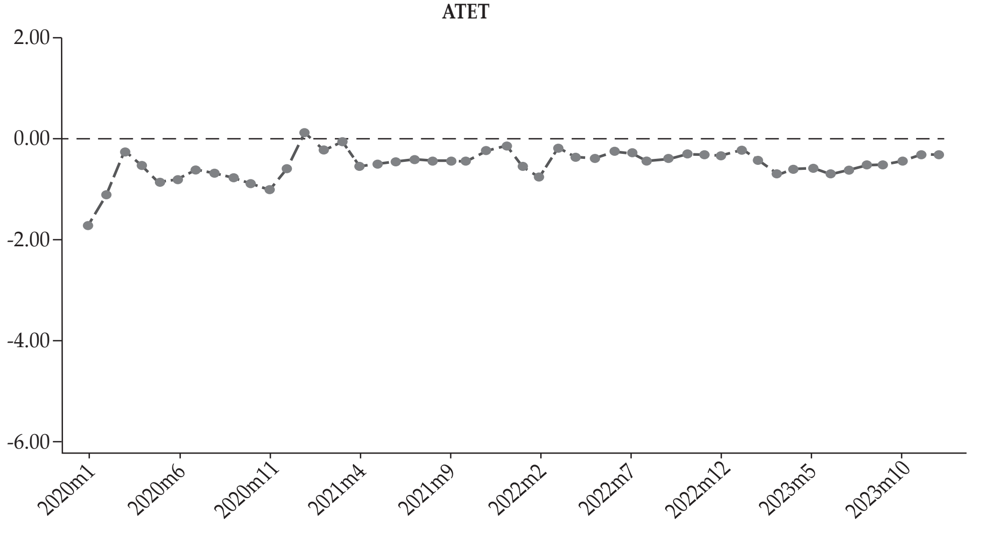
Source: Author's analysis

We can see the ATET over the COVID-19 period to the present in Graphs 1, 2, and 3d below for each dependent variable. In Graph 1 (ROA), AI adoption initially has a neutral or slightly negative impact, likely due to adaptation costs, but gradually turns positive, suggesting long-term profitability gains. In contrast, AI chatbot implementation consistently enhances ROA, reflecting improved customer engagement and operational efficiency. In Graph 2 (NPL), AI adoption initially increases bad loans, possibly due to early implementation challenges, but later stabilises near zero, indicating that banks eventually mitigate credit risk. Meanwhile, AI chatbots steadily reduce NPL, suggesting improved loan quality and risk management. In Graph 3 (LDR), AI adoption starts with a slightly negative effect, reflecting early inefficiencies in loan allocation, but later becomes positive, indicating optimised deposit utilisation. The AI chatbot effect on LDR is even stronger, showing a sustained upward trend, likely due to improved customer interactions, deposit growth, and streamlined loan operations. These findings highlight how AI technologies evolve in impact, with AI chatbots showing faster and more consistent benefits across all indicators.

Graph 1.
ATET Over Time for the ROA Variable (Model 16)



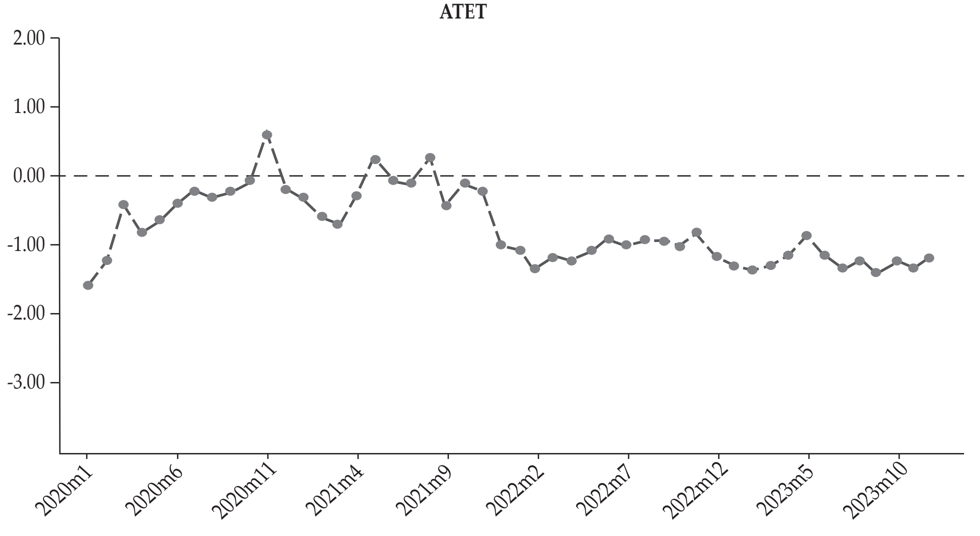
(a) Ai Adoption



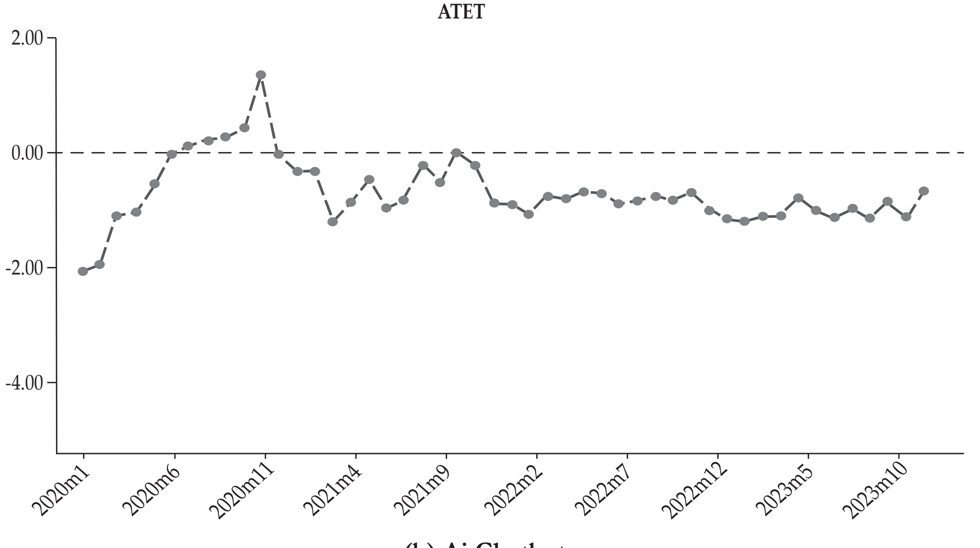
(b) Ai Chatbot

Source: Author's analysis

Graph 2.
ATET Over Time for NPL Variable (Model 17)



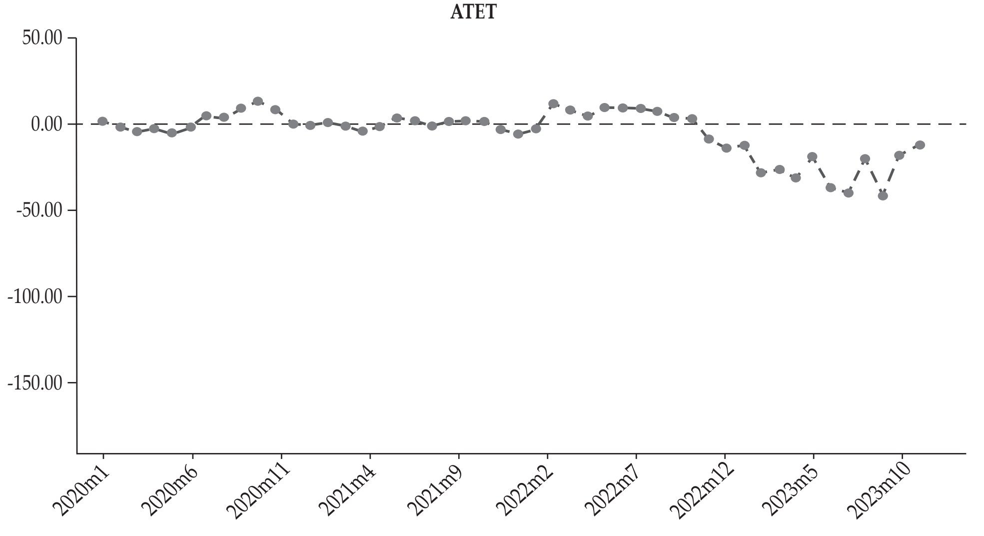
(a) Ai Adoption



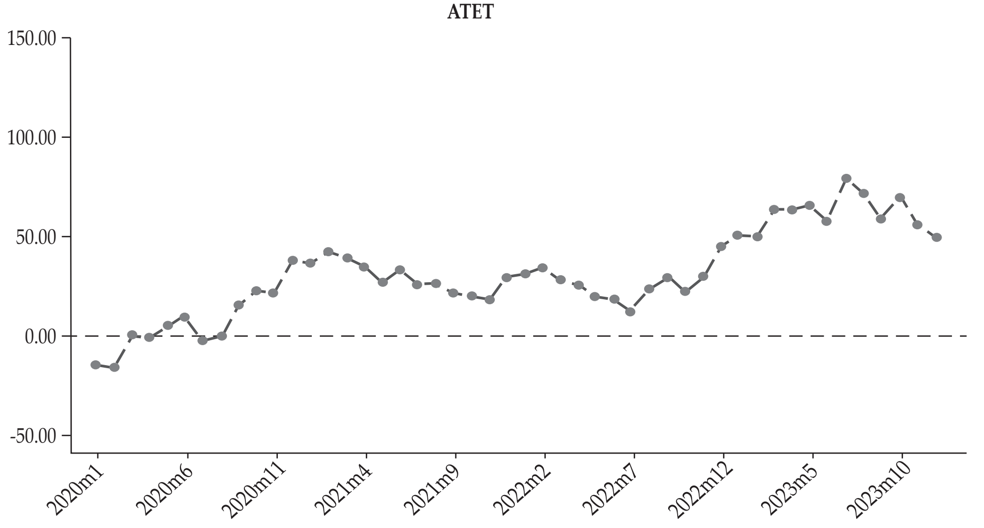
(b) Ai Chatbot

Source: Author's analysis

Graph 3.
ATET Over Time for the LDR Variable (Model 18)



(a) Ai Adoption



(b) Ai Chatbot

Source: Author's analysis

IV.C. System Dynamics Analysis

IV.C.1 Development Causal Loop Diagram (CLD) of the Model

In modelling the CLD, AI Implementation is the main variable affecting banks' financial performance through two channels. First, AI Implementation will affect profitability through gross profit, operating profit, income before tax, and net income as depicted in the reinforcing loop (R3). This improvement in financial performance can be explained through three main mechanisms:

(1) AI facilitates the analysis of large and complex datasets, enabling policymakers to identify patterns and trends that can support more targeted and informed policymaking;[45]

(2) AI training for banking workers improves their performance;[46]

(3) AI improves client service quality[47] through, for example. the use of chatbots.

Secondly, AI Implementation will also increase operating expenses, which in turn reduce operating profits, as seen in the balancing loop (B6). In addition, AI Implementation can also reduce human involvement, which in turn increases the risk of job loss for workers, as seen in the balancing loop (B5).[48] A more detailed CLD is shown in Figure 3.

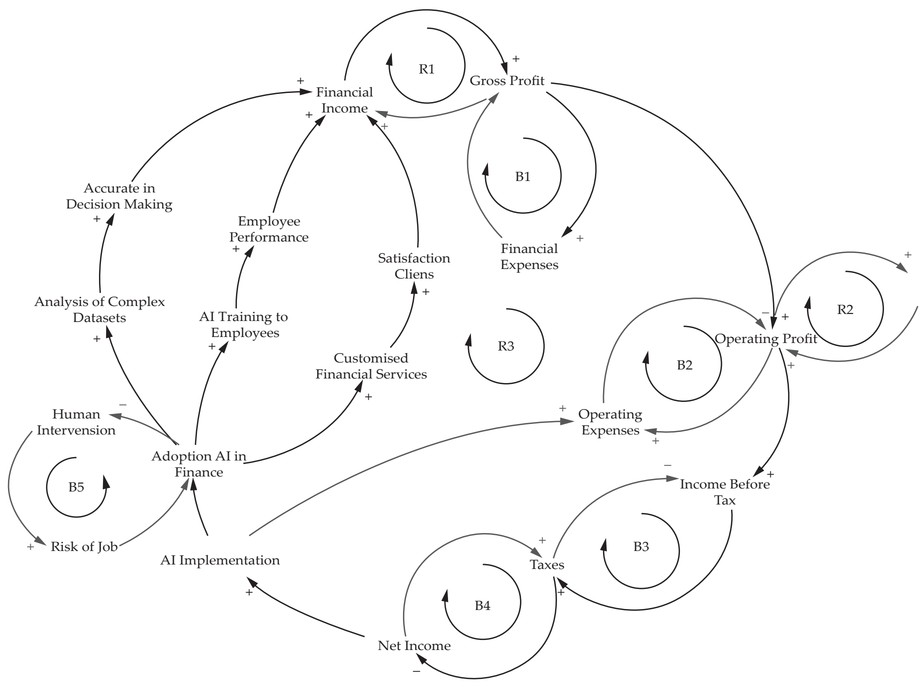
[45] Oxford Analytica, "AI's Promise to Improve Policy-Making Comes with Risks," *Expert Briefings* (2024): 1–2, https://doi.org/10.1108/OXAN-DB291026.

[46] K.K. Ramachandran et al., "Machine Learning and Role of Artificial Intelligence in Optimizing Work Performance and Employee Behavior," *Materials Today: Proceedings* 51 (2022): 2330-2331, https://doi:10.1016/j.matpr.2021.11.544.

[47] Taqwa Hariguna and Athapol Ruangkanjanases, "Assessing the Impact of Artificial Intelligence on Customer Performance: A Quantitative Study Using Partial Least Squares Methodology," *Data Science and Management* 7, no. 3 (2024): 155–157, https://doi.org/10.1016/j.dsm.2024.01.001.

[48] Mohamad H. Soueidan and Rodwan Shoghari, "The Impact of Artificial Intelligence on Job Loss: Risks for Governments," *Technium Social Sciences Journal* 57 (2024), 206-223, https://doi:10.47577/tssj.v57i1.10917.

Figure 3.
Causal Loop Diagram



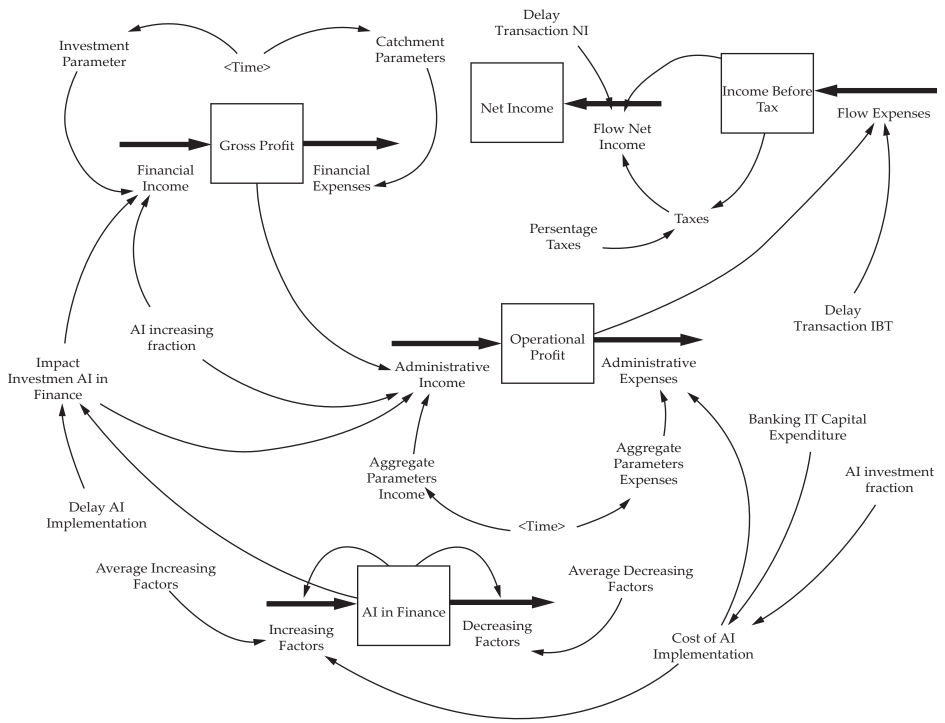
Source: Author's analysis

IV.C.2 Development Stock and Flow Diagram (SFD) of the Model

Based on the results of the previous Causal Loop Diagram (CLD), a Stock and Flow Diagram (SFD) can be constructed as shown in Figure 5. In this SFD, there are five submodels, each representing the dynamics of banking business behaviour based on the stock being modelled.

The first stock in this model, AI in Finance, represents the accumulation of AI investment in the banking sector. The inflow to this stock is influenced by average growth factors, including cost reduction, revenue growth, and improved worker performance resulting from AI implementation. Additionally, the inflow is also determined by AI implementation costs, estimated at 20% of Banking IT capital expenditure, based on findings from the McKinsey Global Survey on AI. This survey indicates that more than one-third of high-performing institution allocate over 20% of their digital budgets to AI adoption. Conversely, the outflow of AI in Finance is governed by the average decreasing factors, which account for job losses due to automation and the subsequent reduction in labour demand.

Figure 4.
Stock and Flow Diagram



Source: Author's analysis

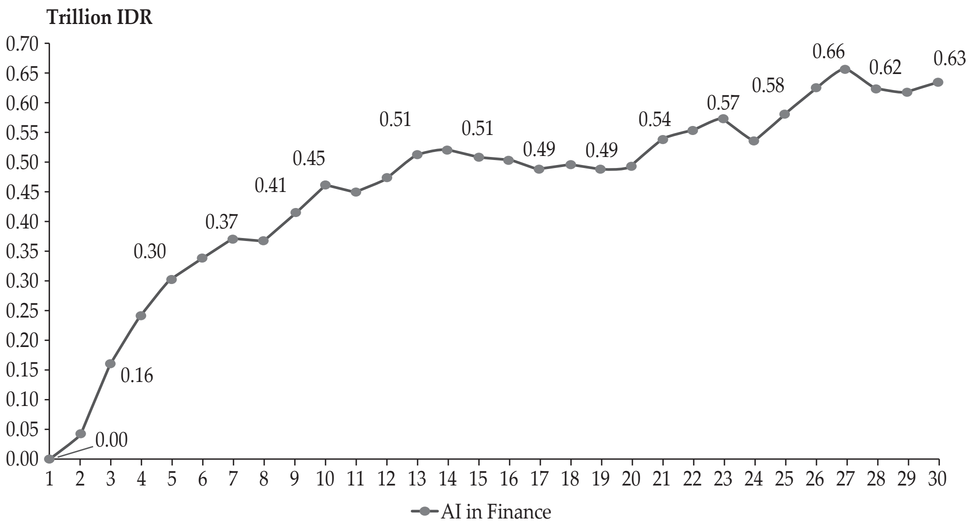
The second stock, Gross Profit, is primarily driven by income, with additional influence from AI investments in the banking sector. Since AI adoption requires time for integration and efficiency realisation, this study incorporates a smooth-type delay mechanism to ensure a gradual rather than immediate impact. This delayed effect reflects the time required for AI-driven adjustments to financial operations. Meanwhile, the outflow from Gross Profit stock is determined by catchment parameters, representing factors that reduce profitability over time. Similarly, the third stock, Operational Profit, receives inflows from administrative income, which consists of two primary components: aggregate parameter income and the Impact of AI Investment in Finance, calculated as 5% of AI investment. This model assumes that AI enhances operational efficiency by reducing administrative costs, thus positively influencing profitability. The outflow consists of administrative expenses incurred by banking institutions.

Finally, the fourth stock, Income Before Taxes, receives inflows from Operational Profit, while the fifth stock, Net Income, is determined after deducting tax liabilities. Both stocks incorporate a fixed-delay mechanism to account for the lag in financial reporting and transaction recording. This assumption aligns with standard accounting practices, where financial statements require processing time before reflecting value changes in the system. By incorporating these delay mechanisms, the model accurately captures the temporal effects of AI investment on financial performance, ensuring a realistic representation of banking sector dynamics.

IV.C.3 System Dynamics Behavioural Analysis

After the Stock and Flow Diagram (SFD) was constructed, simulations were conducted over a period of 30 months using two scenarios, namely (i) a scenario with AI adoption represented by the AI in Finance submodel, and (ii) a comparison scenario without AI adoption. The simulation results show that AI investment increased gradually over the simulation period and exhibited a steady upward trend with only minor fluctuations, as shown in **Graph 4**. This pattern reflects a reinforcing feedback mechanism, whereby the accumulation of AI capabilities encourages further investment and confirms that AI adoption in the banking sector is progressive rather than instantaneous.

Graph 4.
AI in Finance - 30 Month Simulation

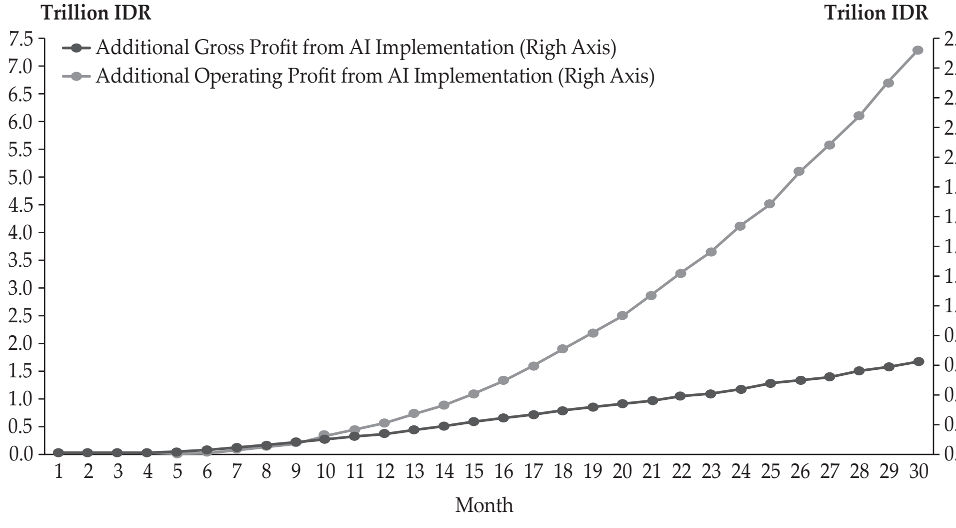


Source: Author's analysis

To evaluate the impact of AI adoption on bank financial performance, differences in profitability indicators—gross profit, operating profit, income before taxes, and net income—were compared between the two scenarios. The simulation results presented in **Graph 5** and **Graph 6** show a non-linear adjustment pattern. In the early stages, AI adoption generated relatively modest profitability gains due to the initial operational costs and technological adjustments processes. However, over time, these gains accelerated and translated into increasingly strong performance improvements. Gross profit begins to show better performance relative to the scenario without AI in the early phase, whereas operating profit, income before tax, and net income exhibit a more gradual increase over time. This difference in the speed of performance improvement reflects the existence of a delay mechanism in the system, including administrative costs, reporting processes, and tax obligations, which cause the benefits of AI to be realised only gradually.

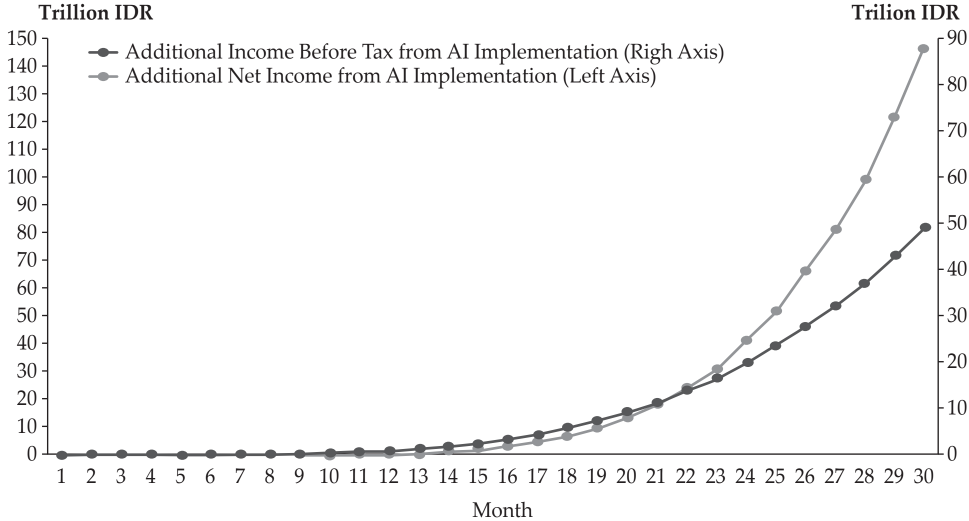
To test the robustness of this behaviour pattern, a simple sensitivity analysis was conducted by varying several key parameters in the model. Specifically, the portion of banking IT capital expenditure allocated to AI investment was varied within a reasonable range (15–25 per cent), and the parameter for cost reduction due to AI efficiency was adjusted by ±20 per cent from the base value. The simulation results show that, despite differences in the magnitude and timing of performance recovery, all scenarios exhibit a consistent pattern: a decline in profitability in the early phase, followed by sustained improvement in performance in the medium and long term. These findings indicate that the "initial dip–then exponential gain" pattern is structural in the model and does not depend on specific parameter values, thereby reinforcing the validity of the dynamics generated by the System Dynamics framework.

Graph 5.
The Impact of AI Adoption on Gross Profit and Operating Profit Performance



Source: Author's analysis

Graph 6.
The Impact of AI Implementation on Income Before Taxes and Net Income Performance



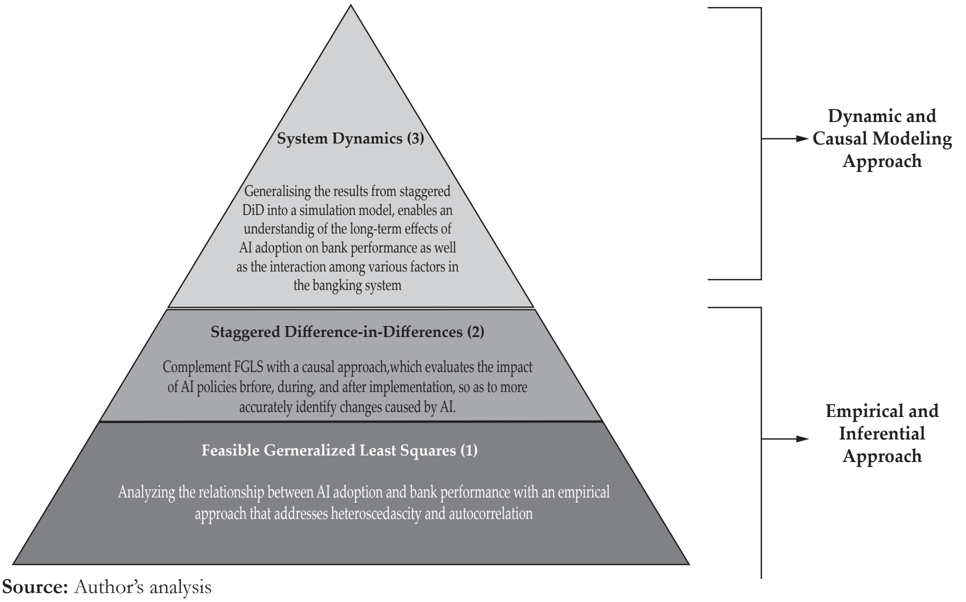
Source: Author's analysis

V. DISCUSSION AND RECOMMENDATION

After using the empirical approach via FGLS and Staggered DID, as well as the dynamic approach and causal modelling via System Dynamics, the following findings are synthesised. This pattern of analysis is consistent with Figure 5, where each method is complementary in providing a more comprehensive understanding.

The FGLS approach reveals that AI Adoption and AI Chatbot positively contribute to banking performance by increasing ROA and optimising risk management through decreasing NPL and LDR. The implementation of AI in the banking system enables automation in financial service processes and risk mitigation, which in turn can improve overall operational efficiency. However, investment in AI training had a negative impact on ROA and an insignificant impact on NPL. This suggests that implementation costs and the time required for technology adaptation may lead to temporary inefficiencies before the benefits are fully realised. In contrast to AI Training, the benefits of AI Adoption and AI Chatbot directly contribute to increased profitability through service efficiencies, such as implementing AI-based credit scoring and optimising credit risk evaluation. Thus, while AI technology has great potential to improve banking performance, its adoption remains dependent on the institution's internal readiness.

Figure 5.
Results Framework



Source: Author's analysis

Although FGLS can identify the direct relationships among observed variables, this approach cannot capture the dynamics before and after AI policies are implemented. Therefore, further analysis using Staggered DiD is conducted to evaluate the policy impact more comprehensively over time. The estimation results show that there are differences in bank performance in three periods: before, during, and after COVID-19, especially for banks that have adopted AI.

1. Before COVID-19, AI adoption contributed positively to bank performance. AI adoption significantly increased ROA (January 2018 cohort) and decreased NPL (March 2018 and December 2018 cohorts) and decreased LDR (January 2018 cohort).
2. During COVID-19, bank performance has decreased. AI Adoption and AI Chatbot actually had a negative impact by significantly reducing ROA. In addition, NPLs increased significantly in the February 2020 cohort, and LDR increased significantly in the March 2020 cohort.
3. After COVID-19, bank performance started to improve. ROA increased again in the August 2023 cohort for AI Adoption and AI Chatbot. However, LDR has not shown any improvement.

The impact of AI adoption on bank performance is dynamic and influenced by economic conditions. Before COVID-19, AI improved operational efficiency, credit scoring, and liquidity management, leading to higher ROA, lower NPLs, and stable LDR. However, during the pandemic, credit risk and liquidity shocks increased, and AI, relying on historical data, struggled to adapt, causing ROA to decline and NPL and LDR to rise. Notably, in December 2019, AI adoption was significantly negatively related to LDR (-160.93***), likely reflecting banks' pre-emptive liquidity adjustments. While Staggered DiD tracks changes over time, it lacks insights into causal relationships, feedback loops, and delays, prompting the use of SD. SD simulations show initial stagnation in profitability in the short term due to high AI investment costs, but as AI enhances data analysis, decision-making, and risk management, profits increase exponentially, offsetting early expenses and driving long-term financial gains. Based on the discussion, policy recommendations were made as shown in Table 11.

Table 11.
Policy Recommendation

Recommendations	Short Term	Medium-Long Term	Stakeholders
Optimising AI Implementation for Operational Efficiency	Increase the adoption of AI in banking services such as chatbots, recruitment processes, fraud detection, etc. to improve service efficiency and customer satisfaction.	Development of more sophisticated AI with predictive analytics technology and utilisation of big data to support strategic decision making and increase Capital Expenditure allocation for IT.	Banking, Bank Indonesia, OJK, AI Technology Providers
Credit Risk Mitigation and Liquidity Management through AI	Using AI for credit scoring and risk analysis to reduce NPL and LDR levels.	Integration of AI with big data to improve the accuracy of credit risk prediction and adaptation of AI models based on dynamic economic patterns.	Bank, Bank Indonesia, OJK, Data and Technology Provider, LPS
Policy Adaptation to Technology Trends	Adjust banking policies with the results of the initial evaluation of AI implementation	Develop flexible regulations that allow banks to innovate in AI without compromising financial stability.	Bank Indonesia, Financial Regulator, OJK, Ministry of Finance
Effective Investment in AI Training	Allocate funds for workforce training to improve skills in AI operations.	Developed continuous AI training curriculum to improve human resources readiness for banking automation.	Banks, Bank Indonesia, OJK, Educational Institutions, Technology Providers

Source: Author's analysis

VI. CONCLUSION

This study analyses the impact of AI adoption on bank performance and financial stability in Indonesia using a combination of empirical and simulation approaches. Using monthly panel data from 50 banks for the period 2017–2023, this study applies FGLS with Driscoll Kraay robustness checking and staggered DiD to identify the causal effects of AI adoption, complemented by SD modelling to capture medium and long-term dynamics. This approach allows for a more comprehensive evaluation of the short-term performance implications and the sustainability of AI's impact on the banking system.

The results of the empirical analysis using FGLS and staggered DiD show that the impact of AI on bank performance is selective and depends on the form of its implementation. The adoption of AI in general, and the use of AI chatbots, have been shown to increase profitability (ROA), reduce credit risk (NPL), and improve intermediation efficiency, as reflected in a decrease in LDR. Conversely, AI training does not show a consistent impact on key performance indicators, with no significant effect on NPL, and is only associated with short-term decreases in ROA and LDR. These findings indicate that AI training reflects more of an investment and organisational adjustment phase rather than an immediate measurable improvement in performance. Staggered DiD estimates also show that the benefits of AI weakened during the COVID-19 pandemic period due to macro and liquidity pressures, before stabilising again in the post-pandemic phase. The results of the System Dynamics simulation are consistent with these findings, showing a trade-off between the initial costs of AI implementation and gradually increasing profits over the long term.

From a policy perspective, these findings underscore the importance of a cautious approach for Bank Indonesia and supervisory authorities in responding to AI adoption in the banking sector. AI implementation needs to be understood as a gradual process with different risk implications at each phase, so that risk-based supervision and macroprudential policies need to distinguish between the adoption of operational technology and investment in human resource capabilities. Furthermore, the results of this study also highlight the need for a regulatory framework that ensures AI-based efficiency does not compromise the resilience of the financial system.

This study has limitations, particularly regarding the measurement of AI adoption, which is still based on dummy indicators, the potential for omitted variables and macro shocks in the observational design, and structural assumptions in the System Dynamics model. Further research is recommended to develop more granular AI measures, explore additional causal identification strategies, and explicitly integrate macroprudential policy scenarios into dynamic simulations. Also, although the staggered DiD estimator by Callaway and Sant'Anna was applied to address treatment timing heterogeneity, the parallel trends assumption that is essential for causal identification, cannot be conclusively verified without such graphical evidence. If pre-treatment trends were not parallel, the estimated effects of AI adoption could be confounded by time-varying, unobserved factors, introducing potential selection bias

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APPENDIX

Appendix 1.
List and name of the banks to use as sample

1.	BANK OF AMERICA, N.A	21.	PT BANK INDEX SELINDO	41	PT BANK SBI INDONESIA
2.	CITIBANK NA	22.	PT BANK JASA JAKARTA	42	PT BANK SEABANK INDONESIA
3.	MUFG Bank, Ltd*	23.	PT BANK KEB HANA INDONESIA	43	PT BANK SHINHAN INDONESIA
4.	PT ALLO BANK INDONESIA Tbk	24.	PT BANK MANDIRI (PERSERO), Tbk*	44	PT BANK SINARMAS, Tbk
5.	PT BANK ANZ INDONESIA	25.	PT BANK MANDIRI TASPEN	45	PT BANK TABUNGAN NEGARA (PERSERO), Tbk
6.	PT BANK BTPN, Tbk	26.	PT BANK MASPION INDONESIA	46	PT BANK UOB INDONESIA
7.	PT BANK BUMI ARTA, Tbk*	27.	PT BANK MAYBANK INDONESIA, Tbk	47	PT BANK WOORI SAUDARA INDONESIA 1906, Tbk
8.	PT BANK CENTRAL ASIA, Tbk*	28.	PT BANK MEGA, Tbk*	48.	PT KROM BANK INDONESIA Tbk
9.	PT BANK CHINA CONSTRUCTION BANK INDONESIA, Tbk	29.	PT BANK MESTIKA DHARMA	49	PT PAN INDONESIA BANK, Tbk
10.	PT BANK CIMB NIAGA, Tbk*	30.	PT BANK MIZUHO INDONESIA	50	PT Super Bank Indonesia
11.	PT BANK COMMONWEALTH*	31.	PT BANK MULTIARTA SENTOSA		
12.	PT BANK CTBC INDONESIA*	32.	PT BANK NAGARI		
13.	PT BANK DANAMON INDONESIA, Tbk*	33.	PT BANK NEGARA INDONESIA (PERSERO), Tbk*		
14.	PT BANK DBS INDONESIA	34.	PT BANK OCBC NISP, Tbk*		
15.	PT BANK GANESHA	35.	PT BANK OKE INDONESIA TBK*		
16.	PT BANK HIBANK INDONESIA	36.	PT BANK PERMATA, Tbk*		
17.	PT BANK HSBC INDONESIA*	37.	PT BANK RAKYAT INDONESIA (PERSERO), Tbk		
18.	PT BANK IBK INDONESIA Tbk	38.	PT BANK RAYA INDONESIA TBK		
19.	PT BANK ICBC INDONESIA*	39.	PT BANK RESONA PERDANIA		
20.	PT BANK INA PERDANA*	40.	PT BANK SAHABAT SAMPOERNA*		

Source: Author's analysis

The banks listed above constitute the final sample used to evaluate the impact of artificial intelligence adoption on banking performance. AI implementation was operationalized through three modalities: chatbot deployment, AI-focused training programs, and broader adoption initiatives. Treatment status was assigned based on documented evidence extracted from bank annual reports and contemporaneous news articles. Banks marked with an asterisk (*) represent the not-yet-treated control groups, meaning they were identified as AI adopters at a later point during the sample period. In contrast, banks without an asterisk were not found to have implemented AI through 2023, based on the authors' review, and thus serve as the untreated comparison group throughout the analysis period.

Appendix 2.
Driscoll-Kraay Estimation for The AI Impact to ROA

	Model 1		**Model 2**		**Model 3**	
	ROA	**ROA**	**ROA**	**ROA**	**ROA**	**ROA**
Ai Adoption	-0.380***	-0.276***				
	(0.103)	(0.104)				
Ai Chatbot			-0.088	0.009		
			(0.064)	(0.074)		
AI_training					0.101	0.119
					(0.113)	(0.112)
CAR		-0.009***		-0.009***		-0.009***
		(0.002)		(0.002)		(0.002)
INK		5.202*		5.207*		5.208*
		(2.785)		(2.786)		(2.785)
SB_DEP_RP		0.035		0.047*		0.047*
		(0.024)		(0.025)		(0.024)
loandemand		-0.281		-0.278		-0.279
		(0.219)		(0.208)		(0.209)
GDPRiil100		0.022		0.022		0.022
		(0.019)		(0.019)		(0.019)
_cons	1.620***	1.682***	1.575***	1.571***	1.567***	1.572***
	(0.047)	(0.170)	(0.054)	(0.173)	(0.056)	(0.173)
Observations	4200	4200	4200	4200	4200	4200

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
Source: Author's analysis

Appendix 3.
Driscoll-Kraay Estimation for The AI Impact to LDR

	Model 4		Model 5		Model 6	
	LDR	LDR	LDR	LDR	LDR	LDR
Ai Adoption	-20.870***	-13.935***				
	(3.965)	(3.332)				
AI_chatbot			-11.169***	-2.262***		
			(1.465)	(0.846)		
AI_training					-0.512	1.230
					(2.732)	(2.671)
CAR		0.638***		0.644***		0.645***
		(0.197)		(0.197)		(0.197)
INK		25.150		25.408		25.413
		(23.717)		(24.348)		(24.421)
SB_DEP_RP		5.220***		5.734***		5.807***
		(0.846)		(0.876)		(0.879)
loandemand		3.112		3.249		3.280
		(3.464)		(3.337)		(3.352)
GDPRiil100		-0.120		-0.085		-0.087
		(0.316)		(0.305)		(0.305)
_cons	99.791***	49.811***	97.876***	44.971***	96.912***	44.327***
	(1.652)	(9.502)	(1.545)	(9.935)	(1.582)	(10.020)
Observations	4200	4200	4200	4200	4200	4200

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
Source: Author's analysis

Appendix 4.
Driscoll-Kraay Estimation for The AI Impact to NPL

	Model 7		Model 8		Model 9	
	NPL	NPL	NPL	NPL	NPL	NPL
AI_adoptionion	-0.054	-0.161				
	(0.207)	(0.199)				
AI_chatbot			0.042	-0.055		
			(0.122)	(0.120)		
AI_training					-0.094	-0.121
					(0.100)	(0.099)
CAR		-0.006***		-0.006***		-0.006***
		(0.001)		(0.001)		(0.001)
INK		-8.722***		-8.719***		-8.720***
		(2.107)		(2.105)		(2.105)
SB_DEP_RP		-0.082***		-0.077***		-0.076***
		(0.022)		(0.025)		(0.025)
loandemand		0.296		0.297		0.300
		(0.213)		(0.217)		(0.220)
GDPRiil100		-0.019		-0.019		-0.019
		(0.020)		(0.020)		(0.020)
_cons	2.827***	3.570***	2.815***	3.522***	2.819***	3.508***
	(0.056)	(0.145)	(0.050)	(0.161)	(0.053)	(0.172)
Observations	4200	4200	4200	4200	4200	4200

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*
Source: Author's analysis